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Assessing the sustainability of renewable energy technologies using multi-criteria analysis: Suitability of approach for national-scale assessments and associated uncertainties

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ABSTRACT

Multi-criteria analyses (MCAs) are often applied to assess and compare the sustainability of different renewable energy technologies or energy plans with the aim to provide decision-support for choosing the most sustainable and suitable options either for a given location or more generically. MCAs are attractive given the multi-dimensional and complex nature of sustainability assessments, which typically involve a range of conflicting criteria featuring different forms of data and information. However, the input information on which the MCA is based is often associated with uncertainties. The aim of this study was to develop and apply a MCA for a national-scale sustainability assessment and ranking of eleven renewable energy technologies in Scotland and to critically investigate how the uncertainties in the applied input information influence the result. The developed MCA considers nine criteria comprising three technical, three environmental and three socio-economic criteria. Extensive literature reviews for each of the selected criteria were carried out and the information gathered was used with MCA to provide a ranking of the renewable energy alternatives. The reviewed criteria values were generally found to have wide ranges for each technology. To account for this uncertainty in the applied input information, each of the criteria values were defined by probability distributions and the MCA run using Monte Carlo simulation. Hereby a probabilistic ranking of the renewable energy technologies was provided. We show that the ranking provided by the MCA in our specific case is highly uncertain due to the uncertain input information. We conclude that it is important that future MCA studies address these uncertainties explicitly, when assessing the sustainability of different energy projects to obtain more robust results and ensure better informed decision-making.

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1. Introduction

Renewable energy markets and policy frameworks are evolving rapidly throughout the world in response to a number of global challenges and concerns, including climate change, increasing energy demand and energy security [1]. Governments and policy-makers are introducing legislation and support mechanisms to accelerate the development of the renewable energy sector, and many countries now have ambitious targets for renewable energy generation and addressing carbon emissions. For example, Scotland has set a target of generating the equivalent of 100% of Scottish demand for electricity and 11% of heat capacity from renewable sources by the end of 2020 [2].

To meet renewable energy and carbon emission targets in a sustainable fashion, it is important to understand and assess the full environmental footprint as well as the trade-offs between the benefits and dis-benefits associated with various renewable energy technologies. The selection of the most suitable renewable energy technology for a given area or location is typically faced with a range of conflicting environmental, socio-economic and technical criteria. For example, the benefits may include a reduction in greenhouse gas emissions and decreasing the reliance on non-renewable sources of energy, while the dis-benefits could be that the renewable technology is very costly, or has adverse impacts on landscapes or habitats. There is a need for approaches that can address these conflicts and trade-offs when assessing which renewable energy technology is most sustainable and appropriate at a given location.

A popular approach for investigating and assessing the full environmental impacts from a given product is life-cycle analysis (LCA). LCA attempts to assess the environmental impacts associated with all the stages of a product's life from-cradle-to-grave, i.e. from mining and processing of raw materials to manufacture, distribution, use, repair and maintenance, and disposal and/or recycling. LCA has been used widely for investigating and comparing the full environmental footprint of different energy generating systems, including renewables (e.g., [3–9]). However, LCA typically only considers known and quantifiable environmental impacts such as greenhouse gas emissions, while e.g. socio-economic implications of the product generally are not accounted for, although recent developments have attempted to complement the more traditional environmental LCA with social aspects (e.g., [10–12]). However, integration of the environmental, economic and social “dimensions” within an LCA framework is still to be developed.

When evaluating the sustainability of different renewable energy generation technologies, there is a range of important indicators and criteria that needs to be considered [13]. Multi-criteria analysis (MCA) is useful for problems in which there are a finite number of alternatives to be assessed on the basis of a range of conflicting criteria featuring different forms of data and information. MCA is becoming an increasingly popular method for addressing the multi-dimensional and complex nature of sustainability assessments. It has been widely applied for assessing and comparing the sustainability of different renewable energy technologies, plans and policies [14], both in specific areas or regions (e.g., [15–18]), but also for more generic assessments (e.g.,[19,20]).

The outcome of any MCA will generally depend on the selected criteria on which the different alternatives are assessed, the weights assigned to the criteria, and the specific method used for ranking the alternatives based on how well they perform given the criteria. Typically it is assumed that all criteria and their respective weights can be expressed as crisp values, in which case the ranking of the alternatives is straightforward. However, in real-world sustainability assessments of renewable energy alternatives, both the input data for the different alternatives and the weighting of the criteria will often be associated with significant uncertainties. For example, Evans et al. [13] found that the greenhouse gas emissions (in kg $CO_{2\text{-eq}}$/kW h) and the price of electricity generation (in USD/kW h), which are two of the most commonly applied criteria in MCAs of renewable energy developments, varied widely for each of the four renewable energy technologies considered in their study. Such uncertainty may significantly influence the outcome of a MCA and lead to a much less clear-cut ranking of the alternatives. However, many of the existing MCA studies of different renewable energy alternatives do not explicitly consider the uncertainties associated with input values and/or the weighting of criteria. In some studies uncertainty is acknowledged by e.g. carrying out a sensitivity analysis or scenario analysis of the criteria weighting (e.g., [19–21]) or by carrying out the MCA using multiple approaches (see e.g. review in [22]) as a way to check the robustness of the results. Other studies address the uncertainties in MCA by using fuzzy logic, where certain input values and/or the weights are defined as fuzzy variables (e.g., [23–25]). Fuzzy approaches have proven useful for handling the more qualitative information and subjective judgements going into a MCA, which are often expressed in linguistic terms such as “weak”, “moderate”, “strong” and “very strong” [26].

This study intends to critically appraise the MCA method for assessing, comparing and ranking different renewable energy technologies based on a range of uncertain sustainability indicators. The aim of this study is therefore twofold: first, to develop and apply a MCA to assess the sustainability and rank eleven renewable energy technologies at a national scale, using Scotland as an example; and second, to investigate how the uncertainties in the applied input information may influence the results of such a ranking exercise. The specific contributions of this work can be summarised as follows: (i) we develop and present a MCA for national-scale assessment of renewable energy technologies. The developed MCA is based on the widely used PROMETHEE method (Preference Ranking Organization Method of Enrichment Evaluation) [27] and considers nine commonly adopted sustainability criteria; (ii) we provide extensive literature reviews for each of these criteria to determine best estimates and assess the variability/range of the input criteria values, and we feed this information into the MCA to provide a ranking of the selected renewable energy alternatives; and (iii) because the applied input information is found to be very uncertain, we modify the PROMETHEE method to account for the uncertainty in the criteria values by using Monte Carlo simulation. We hereby provide a probabilistic ranking of the considered technologies and directly demonstrate how the variability in the input information affects the outcome of the MCA. We are of the opinion that uncertainty needs to be

considered as part of effective decision-making with different degrees of uncertainty being acceptable for different types of decisions. By explicitly including uncertainties in the MCA we believe the output is more robust for effective decision-making.

2. The PROMETHEE method

The multi-criteria analysis is here carried out using the PROMETHEE method developed by Brans et al. [27]. Briefly, the basis of PROMETHEE is an evaluation table, where a finite number N of alternatives $A=[a_1, a_2,\ldots,a_N]$ are evaluated for a finite number P of evaluation criteria $C=[c_1(\cdot),c_2(\cdot),\ldots,c_P(\cdot)]$. The different alternatives are compared pairwise by considering the deviation between the evaluations of two alternatives on a particular criterion. Based on this deviation, the decision-maker assigns a preference to the best alternative (under that given criteria) expressed by a number between 0 (indicating no preference or indifference) and 1 (indicating outright preference). For small deviations, a small preference to the best alternative is allocated (or possibly even no preference if the deviation is considered negligible), while larger preferences are assigned to larger deviations.

The preference of alternative a_1 over alternative a_2 for a particular criteria c_j can be determined by means of a preference function $P_j(a_1,a_2)$, which expresses the preference as a function of the deviation $d_j(a_1, a_2)$ between a_1 and a_2 on that particular criterion:

$$P_j(a_1,a_2)=F_j[d_j(a_1,a_2)]=F_j[c_j(a_1)-c_j(a_2)] \tag{1}$$

where F_j is a function of the deviation and ensures that $0\le P_j(a_1, a_2)\le 1$. Fig. 1 shows an example of such preference function, which depends on the parameters q_j and p_j that have to be defined for each criterion considered. The q_j parameter can be seen as an indifference threshold and is the largest deviation, which is considered negligible by the decision maker. The p_j parameter can be seen as an outright preference threshold and is the smallest deviation, which is considered sufficient to generate a full preference [27].

Besides defining the preference functions P_j, the decision-maker must also specify weights to each criterion. These weights w_j are non-negative numbers that represent the relative importance of the different criteria used for the assessment. The higher the weight assigned to a criterion is, the more important that criterion becomes. The weights should be specified so that they reflect the priorities and perceptions of the decision-maker, or the person/people they are representing.

In order to express the degree to which one alternative is preferred over another when considering all the criteria collectively, the index of preference Π is calculated for each pair of alternatives. The index of preference $\Pi(a_1,a_2)$ of alternative a_1 being preferred over alternative a_2 is calculated as the weighted average of the preferences $P_j(a_1,a_2)$ for each criterion as follows:

$$\Pi(a_1,a_2)=\frac{\sum_{j=1}^{P}P_j(a_1,a_2)w_j}{\sum_{j=1}^{P}w_j} \tag{2}$$

$\Pi(a_1,a_2)$ is thus a number between 0 and 1 representing the degree to which a_1 is preferred over a_2 when considering all the criteria, while $\Pi(a_2,a_1)$ represents the preference of a_2 over a_1.

In the PROMETHEE method the so-called "outranking flows" are then calculated in order to rank one alternative against all the other alternatives. The outranking flows for alternative a_1 are given by:

$$\Phi^+(a_1)=\frac{1}{(N-1)}\sum_{b\in A}\Pi(a_1,b) \tag{3}$$

$$\Phi^-(a_1)=\frac{1}{(N-1)}\sum_{b\in A}\Pi(b,a_1) \tag{4}$$

The positive outranking flow $\Phi^+(a_1)$ expresses how the alternative a_1 is outranking all the others, while the negative outranking flow $\Phi^-(a_1)$ expresses how the alternative is outranked by all the others. The higher the $\Phi^+(a_1)$ is and the lower the $\Phi^-(a_1)$ is, the better the alternative a_1 is compared to the other alternatives. A complete ranking of the alternatives can be carried out by calculating the net outranking flow for each alternative, i.e. $\Phi(a_1)=\Phi^+(a_1)-\Phi^-(a_1)$. The alternatives with the highest Φ value are then given the highest rank.

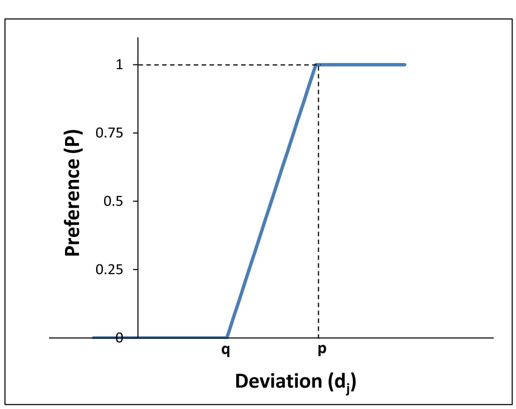
3. Development of MCA for ranking renewable energy technologies in Scotland

3.1. Identification of renewable energy alternatives

The first step in the multi-criteria analysis (MCA) is to identify the alternatives to be compared. Eleven renewable energy technologies have been identified from the Scottish Government's 2020 routemap for renewable energy [2]. These are:

1. Onshore wind can provide electricity at domestic and industrial scales. It is considered a mature and relatively low cost

Preference function type	Definition
Linear function:	



$$P(d_j)=\begin{cases}0 & d_j\le q\\ \dfrac{d_j-q}{p-q} & q<d_j\le p\\ 1 & d_j>p\end{cases}$$

Fig. 1. The linear preference function.

technology with a large supply chain already established. By the end of 2012, Scotland's total installed onshore wind electricity capacity was almost 4000 MW_e [28]. It is expected that onshore wind turbines can make a very large contribution to Scotland's renewable electricity target.
2. Offshore wind can provide electricity at industrial scale. The total installed offshore wind capacity in Scotland was 190 MW_e by the end of 2012 [28]. However, Scotland has an estimated 25% of Europe's offshore wind potential, and offshore wind is therefore expected to make a strong contribution to Scotland's and EU's renewable energy targets.
3. Hydropower can provide electricity at domestic and industrial scales. The technology is considered efficient and has a high level of predictability, the latter especially being the case for conventional and pumped storage hydroelectric schemes. Hydropower is a well-established technology in Scotland with a total electricity capacity of about 1500 MW_e already being installed [28].
4. Wave power can provide electricity at industrial scale. The wave energy sector is still at an early stage. The total installed marine (i.e. wave and tidal power) capacity was only 4 MW_e by the end of 2012 [28]. However, Scotland has an estimated 10% of Europe's wave energy potential, and wave power is therefore expected to make a significant contribution to Scotland's longer term renewable energy and carbon reduction targets.
5. Tidal power can also provide electricity at industrial scale. Different tidal power generating methods exist including tidal stream farms, tidal barrages and tidal lagoons [29]. Like wave power, the tidal energy sector is still in its infancy. The tidal energy potential in Scotland is, however, large, and tidal power is therefore expected to make a significant contribution to Scotland's longer term renewable energy and carbon reduction targets.
6. Geothermal power can provide heat and electricity at industrial scale. Deep geothermal power is an emerging technology in Scotland. In Scottish Government [30] deep geothermal is defined as any geothermal source below 100 m in depth and there are currently only two of such geothermal systems operating in Scotland, both of which utilise water from abandoned coal mines at fairly shallow depths (around 100–200 metres) and a heat pump to provide district heating [30].
7. Photovoltaic (PV) can provide electricity at both domestic and industrial scales (PV farms). Despite the solar resource in Scotland being significant [31], the market for solar PV has so far been fairly limited, likely due to the high capital costs associated with PV. By the end of 2012, the installed PV capacity in Scotland was just over 100 MW_e [28,31].
8. Solar thermal can provide heat mainly at domestic scale. The installed solar thermal capacity in Scotland was 28 MW_{th} in 2012, which amounts to about 5% of the total installed renewable heat capacity in Scotland [32].
9. Dedicated biomass (incl. combined heat & power (CHP)) can provide electricity and heat at both domestic and industrial scales. With an installed biomass capacity of around 450 MW_{th} and 115 MW_e about 80% of the renewable heat output in Scotland came from installations which used biomass [28,32]. The biomass comes from land areas dedicated to the growth of the source material. As an energy source, biomass can either be incinerated directly to produce electricity and/or heat, or it can be converted into other energy products such as biofuel and biogas using e.g. anaerobic digestion, pyrolysis or gasification. The energy output and impacts from biomass are very dependent on the specific feedstock used as well as the technology applied to extract the energy. However, to maintain a manageable number of renewable technologies it has here been decided to consider the different technologies and feedstocks as one technology.
10. Energy-from-waste (incl. CHP) can provide electricity and heat at both domestic and industrial scales. The energy-from-waste (EfW) technologies are essentially the same as for dedicated biomass. The waste source can be incinerated directly or anaerobically digested to generate electricity and/or heat. As for dedicated biomass, the energy output and impacts from waste are very dependent on the specific waste source used as well as the technology applied to extract the energy. However, to keep a manageable number of renewable technologies, it has been decided to consider EfW as a single technology, which includes waste incineration, anaerobic digestion, landfill gas etc. The installed EfW capacity in Scotland was by 2012 around 160 MW_e and 40 MW_{th} [28,32] with the largest contribution from landfill gas.
11. Heat pumps (HPs) extract low-grade heat from the external environment (air source (ASHP), ground source (GSHP) or water source (WSHP)) and through a compression system produce heat for space or water heating, mainly at domestic scale. Heat pumps can also be run in reverse and hereby provide space cooling (i.e. air conditioning). Although heat pumps rely on electricity to operate, their high co-efficient of performance (COP) means they extract more heat energy from the environment than they use in electricity. The heat power released from an electrically powered heat pump to a building can be typically two or three times larger than the electrical power consumed, corresponding to a system efficiency of 200–300%, as opposed to the 100% efficiency of a conventional electrical heater, in which all heat is produced from input electrical energy. But for heat pumps to be "truly" renewable, the electricity used to run the pumps should be generated from a renewable source. In 2012, the installed heat pump capacity in Scotland was about 50 MW_{th} [32].

3.2. Selecting evaluation criteria

The second step is to identify and select a set of criteria that enable the alternatives to be compared from a specific viewpoint. This step is very critical for the MCA approach and is best to be decided on together with the decision-makers. The number of criteria to use depends on the availability of both quantitative and qualitative information and data relating to the potential criteria.

The literature contains several examples of studies that have used MCA to compare alternative renewable energy technologies (e.g., [15,20,21,33,34]). Based on a literature review, Wang et al. [14] provide a comprehensive list of the typical evaluation criteria used in multi-criteria decision analysis of sustainable energy options. The study by Wang et al. [14] has been used as a basis for formulating the criteria used in the current study. Nine criteria have been selected comprising three technical, three environmental and three socio-economic criteria. The selected criteria are summarised in Table 1 and described in detail in the following sections. The values and associated ranges assigned to the different technologies for each of the selected criteria are given in Table 2. As shown in Table 1, some of the criteria are evaluated using a qualitative scale ranging from 1 to 5, where 1 is the worst score and 5 is the best as detailed in the following sections.

3.2.1. Potential total power generation

A critical and widely used criterion in MCAs of renewable energy technologies is the power generating capacity of the different technologies considered. In some studies this is expressed as the total quantity of conventional fuels, which is

Table 1
Overview of the selected criteria.

Criterion	Type	Unit	**Optimize**[a]	Description
Potential total power generation	Technical	TW h/yr	Maximize	The amount of energy the renewable technology potentially can deliver at a national scale per year
Technology maturity	Technical	Qualitative (1–5)	Maximize	State-of-the-art of the technology. How widespread the technology is at both national and European level
Reliability of energy supply	Technical	Qualitative (1–5)	Maximize	The stability and predictability of the technology, i.e. indicates whether the energy supply is subject to interruptions
Greenhouse gas emissions	Environmental	g CO_2eq/kW h	Minimize	The life-cycle GHG emissions (in equivalent emission of CO_2) from the technology
Impacts on amenity	Environmental	Qualitative (1–5)	Maximize	Other impacts such as the visual, noise and odour nuisances as well as the potential risk to ecosystems
Area requirements	Environmental	m^2/kW	Minimize	Land area needed for the technology
Levelized energy cost (LEC)	Socio-economic	GBP/MW	Minimize	Cost of the energy-generating system. LEC includes all the costs over the system's lifetime (i.e. initial investment, operation and maintenance, fuel cost, and cost of capital) and depends on typical technology characteristics such as efficiency, annual production, service life, energy source utilized, and money cost
Contribution to economy	Socio-economic	Qualitative (1–5)	Maximize	Social and economic effects that are associated with the initiatives, such as creation of new jobs, new supply chain businesses, emerging energy sector businesses, industrial districts etc
Social acceptability	Socio-economic	Qualitative (1–5)	Maximize	Public acceptance of the renewable energy technology/project

[a] Optimize refers to whether a high or a low value for a given criterion is preferred.

Table 2
Best estimate criteria values for each of the renewable technologies considered. Minimum and maximum values are given in brackets.

Renewable technology	Total power generation	Technology maturity	Reliability of supply	GHG emissions	Impact on amenity	Area requirements	Levelized Energy Cost	Contribution to economy	Social acceptance
	[TW h/yr]	[Qual.]	[Qual.]	[g CO_2eq/kW h]	[Qual.]	m^2/kW	£/MW h	[Qual.]	[Qual.]
Onshore wind	45 (25–125)	5 (4–5)	2 (2–4)	15 (5–70)	2 (1–4)	200 (10–1200)	70 (25–125)	3 (2–4)	3 (1–4)
Offshore wind	80 (25–150)	4 (3–4)	3 (2–4)	15 (5–70)	3 (1–4)	200 (10–1200)	110 (50–190)	3 (2–5)	4 (2–5)
Hydro power	10 (6–25)	5 (4–5)	4 (3–5)	20 (2–60)	2 (1–4)	500 (10–6500)	60 (10–130)	3 (2–5)	4 (2–4)
Wave	20 (5–60)	2 (2-3)	3 (2–4)	25 (12–50)	4 (1–4)	150 (10–300)	185 (130–400)	4 (2–5)	4 (2–5)
Tidal	20 (5–50)	2 (2–3)	3 (2–4)	25 (10–80)	3 (1–4)	100 (10–300)	160 (80–350)	4 (2–5)	4 (2–5)
Geothermal	2.5 (1–10)	4 (3–4)	5 (4–5)	40 (10–80)	4 (1–4)	100 (20–1000)	80 (10–200)	3 (2–5)	3 (1–4)
Photovoltaic	20 (2.5–70)	5 (4–5)	2 (1–3)	60 (20–200)	5 (3–5)	150 (10–500)	340 (50–600)	4 (2–5)	5 (4-5)
Solar thermal	11 (2.5–20)	5 (4-5)	2 (1–3)	40 (15–150)	5 (3–5)	40 (10–100)	200 (50–450)	3 (2–4)	5 (4-5)
Dedicated biomass	15 (5–45)	4 (4-5)	4 (3–5)	100 (25–600)	2 (1–4)	4000 (1000–6000)	130 (40–250)	3 (2–5)	3 (1–4)
Energy-from-waste	3 (2–10)	4 (4–5)	4 (3–5)	350 (100–1000)	2 (1–4)	25 (0–50)	80 (50–170)	4 (2–5)	3 (1–4)
Heat pumps	10 (5–20)	4 (4–5)	4 (3–5)	150 (65–280)	5 (3–5)	50 (10–300)	95 (50–190)	3 (2–4)	5 (3–5)

replaced by power generation from the given renewable energy systems (e.g., [15,18,35,36]).

In this study, we are considering how much energy the different technologies could potentially deliver at a national scale per year (in units of TW h/yr) rather than how much the technologies are currently delivering. Estimating the potential future power generation for Scotland is not straightforward and inherently associated with uncertainties. A number of studies present estimates of the theoretical or practical renewable resources by technology in Scotland [2,37–43] or in the UK [44–46], and these estimates have here been used as basis for populating Table 2. MacKay [29] presents calculations of the theoretical maximum energy output from different renewable technologies for the entire UK. Here we have carried out similar calculations specifically for Scotland to supplement and support the estimates found in the reviewed literature.

Table 2 presents the estimates of how much power the different technologies could deliver in Scotland. The most estimates are available for wind, bioenergy and the marine technologies, while fewer are available for solar, geothermal and heat pumps. Offshore wind and onshore wind are generally found to be the technologies that can provide the most power at a national scale followed by solar PV and the marine technologies. However, the reported power generating capacities are very uncertain and are found to range an order of magnitude for most of the technologies. One exception is hydropower, for which a fairly narrow range is found. Hydropower is well-established as a technology in Scotland and already accounts for a significant proportion (about 35%) of the existing renewable electricity output in Scotland [28], but the scope for further hydropower development is limited. The variability in the estimates for each of the technologies can be explained by differences in the underlying assumptions and approaches used, how far into the future the potential power generation is estimated, and whether the estimates are based purely on the available resource, as done in e.g. MacKay [29], or if some practical constraints are considered.

3.2.2. Technology maturity

This criterion essentially reflects the state-of-art of the applied technology and is here assessed based on a qualitative 5-point scale ranging from 1 indicating very low maturity (i.e. the technology is only tested in laboratory) to 5 indicating very high maturity (i.e. commercially mature technology with a solid market position). Several other MCA studies of renewables have used similar qualitative scales for technology maturity (e.g., [15,18,26,35]). Table 2 presents the maturity

scores assigned to each technology and these have been determined based on literature information and through dialogue with relevant stakeholders. Onshore wind, hydropower and solar energy are considered to be the most mature technologies, while the marine technologies are the least mature. Compared to many of the other criteria, the maturity scores are considered less uncertain and have therefore been given narrow ranges.

3.2.3. Reliability of energy supply

Reliability of the energy supply has always been a concern in the energy sector and is often included as a criterion in MCA of renewable energy systems [14]. This criterion typically reflects whether the energy supply is subject to interruptions, e.g. solar panels do not operate during the night, and wind turbines cannot operate when there is no wind or if wind speeds are too high. The presence of such interruptions affects the stability and continuity of the energy supply. The reliability of the energy supply is often evaluated qualitatively (e.g., [15,35,47]) and will here be evaluated using the same ordinal scale as suggested in Tsoutsos et al. [18], which ranges from 1 indicating highly discontinuous activity to 5 indicating stable and continuous activity.

The reliability of the energy system can also be evaluated quantitatively, e.g. through the technology capacity factor (i.e. the ratio of the actual power output to the theoretical maximum power output from the technology over a period of time) and/or the availability factors (i.e. the amount of time that the technology is able to generate energy over a certain period, divided by the amount of the time in the period) (as in e.g., [20,33,48]), or by using operating hours (hours/year) and lifetime of the technology [34].

Table 2 presents the reliability scores assigned to each technology. The least reliable technologies are considered to be solar followed by onshore wind, while geothermal, hydropower, bioenergy and heat pumps are considered to provide the most reliable energy supply. As shown in Table 2, the reliability scores are associated with some degree of uncertainty. The reliability of the energy supply for a given technology will vary depending on a number of factors including the specific location (e.g. solar intensity and the wind fluctuations will vary from location to location) and the exact design, type and scale of the renewable system (e.g. a hydropower scheme can be specifically designed to have a low capacity factor to be able to meet peak demand, but can also be designed to supply a more constant base load [49]). This variability is reflected in the literature, where capacity and/or availability factors are often reported with a range for a given technology [50–52] as well as in the UK energy statistics data provided in DECC [28], where the quarterly capacity factor for e.g. onshore wind has ranged between 17% and 37% over the past few years.

3.2.4. Greenhouse gas (GHG) emissions

This criterion refers to the total greenhouse gas (GHG) emissions from a given renewable energy system and is one of the most widely used criteria when evaluating the sustainability of renewables [14]. Some studies consider the GHG emissions avoided using renewable energy technologies compared to the non-renewable energy technologies they replace, expressed either in either kg CO_2eq/yr (e.g., [18,34]) or in kg CO_2eq per energy unit saved or produced (e.g., [15,53]). Here, we will use estimates of life-cycle GHG emissions from the different renewable technologies, measured in equivalent emission of CO_2 per energy unit produced (g CO_2eq/kW h). In a life-cycle assessment (LCA) of the emissions, all or part of the following life stages of the energy production systems are typically considered: (i) fuel production and transportation to the plant, (ii) facility construction, (iii) facility operation and maintenance, and (iv) dismantling [54].

Life-cycle GHG emission estimates from the considered technologies have here been collated from a recent review by Amponsah et al. [55], the results of which are summarised in Table 2. Onshore and offshore wind, hydropower and marine energy are found to have the lowest lifecycle GHG emissions, while biomass and heat pumps are associated with the highest emissions. The proportion of GHG emissions from the different stages of a plant life-cycle differs by technology. For most of the technologies considered here, the infrastructure component (e.g. commissioning and decommissioning) represents the main contributor to the total GHG emissions, while fuel provision represents the largest contribution for dedicated biomass [55,56]. For heat pumps, most of the GHG emissions are associated with the plant operation stage [5]. The operation stage was also identified as the most carbon intense for a tidal barrage system [57].

Reported GHG emissions are found to vary widely for each of the individual technologies. Life-cycle GHG emission estimates will depend on a number of factors, including:

i) The assumptions adopted within the LCA regarding e.g. accounting rules and systems boundaries [56,58] as well as the technology lifetime and capacity factor [6], e.g., [59].
ii) Regional and national differences e.g. in the electricity grid mix used during manufacturing and/or operation of a given technology, and in the potential amount of energy delivered by a technology (e.g. PV can produce more electricity in sunny regions and will thus emit less CO_2 per delivered kW h in such regions) [59,60].
iii) The size of the renewable system considered. Larger renewable energy plants/systems usually have lower emissions per produced energy unit than smaller systems.
iv) Technological differences. For example, the emissions from bioenergy technologies will depend greatly on the source and supply of biomass in terms of e.g. feedstock type and transport distances as well as on the technology used to produce energy (incineration, anaerobic digestion, pyrolysis, gasification etc.) [61], while emissions from PV will depend on whether amorphous silicon, multi-crystalline silicon, mono-crystalline silicon, ribbon silicon or thin-film cadmium telluride systems are considered.

3.2.5. Impacts on amenity

This criterion accounts for other environmental impacts associated with the renewable energy technologies such as the visual, noise and odour nuisances as well as the potential risk to ecosystems and landscapes. A nice overview of the potential negative environmental impacts of various renewable energy technologies is provided in IPCC [62]. The impacts on amenity are here evaluated using a 5-point scale similar to the one adopted by Beccali et al. [15] ranging from 1 indicating very high impacts to 5 indicating very low or no impacts.

Similar criteria are often included in MCA of renewables e.g. through assessments of the sustainability of other impacts [15,35] or the effects and pressures on the natural environment [e.g., 17, 26, 63]. Cavallaro and Ciraolo [64] consider visual impacts, noise and impacts on ecosystem as three separate criteria in their assessment of different wind energy plants. Others include environmental impacts such as noise and odour as part of a social acceptability criteria (e.g., [13]). Several LCA and MCA studies of renewable energy technologies consider impacts such as eutrophication (due to emissions of PO_4eq) and acidification (due to emissions of SO_2eq) separately (e.g., [4,5,8,47]).

Table 2 shows the impacts on amenity scores assigned to each technology. Heat pumps and solar are considered to have the lowest impact on amenity, while bioenergy, hydropower and onshore wind are considered the least favourable in terms of amenity impacts. The impacts on amenity scores have here been determined based on estimates provided in previous MCA studies [15,17,26,35].

3.2.6. *Area requirements*

Land use requirement is an important criterion to consider as renewable energy developments typically are in competition for land, which may be used for e.g. agricultural, recreational or conservational purposes [13]. Siting renewable energy developments on land which could be used for other purposes can therefore result in economic losses proportional to the value of site. Similar to the MCA study by Beccali et al. [15], the land area required for each of the considered technologies is here assessed and expressed as m^2/kW of installed power.

The area requirement values are shown in Table 2, and have been compiled from a number of studies in the literature [4,15,19,29,48,53,65–67]. Dedicated biomass is by far the technology that requires the most land. EfW is assumed to have very low requirements for land [68]. Although the offshore technologies do not require land when in operation, they may compete with a range of other offshore activities including fishing, shipping and navigation, recreational activities, and extraction of raw materials such as oil, gas and sediments. Offshore wind is therefore assumed to have the same land requirements as onshore wind, while the land requirements for the marine technologies have been estimated based on their power generation capacity per unit sea-floor area [29].

The land area requirement values are generally found to be very uncertain. For example, Beccali et al. [15] report that 10 m^2/kW is required for grid connected wind turbines, while Evrendilek and Ertekin [66] report a value of 1200 m^2/kW for wind. The estimates of land requirements depend on the specific site, geographical conditions and the size of the renewable system investigated, but also on whether the entire life-cycle of the technology (e.g. materials for manufacture, recycling and/or disposal also require land use) or only the land requirement during its operation is considered. The land occupation estimates will also depend on whether opportunities for dual land use are accounted for (e.g. a wind turbine can be built on agricultural land), which effectively reduces the land area required for the technology [48].

3.2.7. *Levelised energy cost (LEC)*

When assessing different renewable energy technologies or plans, the associated costs are obviously very decisive and are considered a key criterion in many of the published MCAs studies. The cost criteria considered in previous studies usually include one or more of the following [14]: investment costs, operation and maintenance (O&M) costs, fuel costs and cost of produced electricity (also termed Levelized Energy Cost).

Here, the Levelized Energy Cost (LEC) is used as a single cost criterion, which expresses the actual cost of a unit of produced or saved energy. LEC is a widely used measure of the cost of the energy-generating system and has also previously been used in MCA (e.g., [15,47,53]). LEC includes all the costs over the systems' lifetime (i.e. initial investment, operation and maintenance, fuel cost, and cost of capital). It is also influenced by the typical characteristics of the technology, such as efficiency, annual production, service life, by the nature of the energy source utilized, and by the money cost. Essentially it is the price at which energy must be generated from a specific source to break even.

LEC values for the different technologies are presented in Table 2 and have been collated from various literature studies and published reports [13,16,50,69–76]. Hydropower and onshore wind have the lowest LEC values, while the solar and the marine technologies have the highest LEC values. For most of the renewable technologies, it is mainly the capital costs that contribute to the overall LEC, while the associated O&M and fuel costs generally are low or negligible. However, for biomass and heat pumps, the fuel and O&M costs contribute significantly to the overall LEC.

The reported LEC values are found to vary widely and depend amongst other things on the installation size, technology characteristics, regional variations in cost and performance, and the assumed discount rates. Future-based estimates also tend to decrease, especially for less mature technologies.

3.2.8. *Contribution to economy*

This criterion estimates the total social and economic impacts that are associated with the renewable energy initiatives such as creation of new jobs and businesses. For many governments and policy-makers job creation is a central motivation for developing and deploying renewable energy technologies, and the potential impact on employment and economy is often included as a criterion in MCA of renewable energy schemes [15,16,18–20,48,77].

Estimating the full economic impacts and total job creation associated with a renewable energy scheme is difficult. The economic impact is not just related to the direct jobs created by the project itself (e.g. for manufacturing, installation, operation and maintenance), but also depends on the indirect job effects (i.e. those employed in supplying the inputs and knowledge to the renewable energy project/industry) as well as so-called induced impacts, which refer to the jobs created when wealth generated by the renewable energy industry is spent elsewhere in the economy, hereby stimulating demand in industries that may be entirely unrelated [78,79]. Studies on job creation from renewable energy projects typically only consider the direct effects [e.g., 80,81]. However, several studies suggest that the combined level of indirect and induced employment for an energy project is likely to be as large as or larger than the direct employment itself [78,82]. Another complicating matter is the fact that many renewable energy projects and schemes are supported through government spending programmes, something which is often ignored when assessing the job creation potential from specific renewables schemes. However, such spending programmes mean that the government must either cut spending elsewhere, raise taxes, or raise borrowing, which may lead to loss of jobs in other sectors. Therefore, despite large gross figures often being found in terms of employment and value added [79], net figures are typically significantly smaller (or even negative) due to replaced investments in e.g. conventional energy technologies as well as due to the dampening effect of the higher cost of renewable energies compared with conventional alternatives [78,83].

Assessments of the employment impact typically distinguish between jobs created for construction, installation, and manufacture (CIM) of a new facility, and jobs for its operation and maintenance. The duration of the CIM is relatively short and the associated jobs will therefore in principle only be short-term, while the jobs for O&M will last throughout the life of the facility. Also, while installation and O&M is carried out domestically, manufacturing may take place abroad in which case no direct domestic employment benefits are created [78]. However, although countries that manufacture, deploy and export renewable energy technologies are likely to generate the largest number of jobs, countries without local and/or export industries will still enjoy employment benefits, as significant shares of renewable

energy jobs exist at the point of project development and installation, as well as in O&M [79].

Similar to the work by Tsoutsos et al. [18], the contribution to local economy is here evaluated using a 5-point ordinal scale ranging from 1 designating no or negative impact on local economy to 5 indicating high and sustained impact on local economy.

Table 2 shows the scores assigned to each technology in terms of contribution to the economy. These scores are based on a range of studies on job creation potential of different renewable energy technologies [80–86] as well as on previous MCA studies of renewable energy in which the contribution to employment is considered, either quantitatively as the number of new jobs created per produced unit of energy or power [15,16,19,20,77], or qualitatively [18,35]. Most of the existing studies seem to suggest that the largest job creation per produced unit of energy can be expected for solar PV and EfW (incl. landfill gas), but both tidal and wave energy have also been assigned high scores as the UK and Scotland are positioning themselves as one of the world leaders within marine energy [2]. It should be noted that the available data on renewable energy jobs and impacts on economy are limited and published numbers are generally weak and associated with large uncertainties. The uncertainties arise amongst other things from difficulties in ascertaining which job creation unit/metric is used as well as what method has been used for deriving the job creation statistics [84]. Many estimates are furthermore derived from countries with large-scale deployment and successful manufacturing industries and are therefore likely to represent upper range values [78,79]. These uncertainties are reflected in the scores assigned in Table 2 (and their associated ranges).

3.2.9. Social acceptability

This criterion is based on an assessment of the public acceptance of the different renewable energy technologies and/or plans. This is a very important criterion as public opposition to the development of new renewable energy facilities and public reluctance to invest in renewable energy remain key obstacles to the expansion of the renewables sector in the UK and a number of other European countries [87].

Assessment of the social acceptability of renewable energy technologies is not straightforward. Despite many existing attitude surveys that generally show high levels of public support for renewable energy in principle, actual projects are often met with local opposition and contribute to numerous requests for planning permission being refused or getting 'stuck' in the planning system; a concept which is commonly referred to as 'NIMBYism' (not in my back yard) [88]. For example, in a UK survey by DECC [89] about 80% indicated that they were supportive of the use of renewable energy, while only around 5% were against. However, in the same study, 56% and 21% reported, respectively, agreeing and disagreeing with the notion that they would be happy to have a large scale renewable energy development in their local area, thereby to some extent reflecting a NIMBY effect. However, the NIMBY concept has been subject to a great deal of criticism in the scientific literature and is by many deemed an oversimplification of the complex processes and factors that are behind local opposition to renewable energy schemes [90]. These studies argue that local opposition to actual renewable energy schemes is not just motivated by self-interest and proximity of the scheme, but is affected by a broader range of factors such as place attachment and identity [e.g., 88], people's belief about the impacts (e.g. environmental, aesthetic, economic, and local/community impacts) of the proposed schemes [91], uncertainty regarding the proposal [e.g., 90], scale of the technology [17] and lack of awareness. This is also reflected by the fact that some surveys and studies have shown that people who live close to an existing renewable energy development are more likely to hold positive attitudes towards the use of renewable energy than those who live far from one [92] and that public responses to energy projects change over time, with the likelihood of more positive responses post-installation in comparison to those beforehand, when project outcomes are less uncertain [93].

The assessment of social acceptability is here based on a qualitative scale ranging from 1 indicating strong general resistance to 5 indicating strong general support.

The social acceptability scores assigned to the different energy technologies are presented in Table 2. The scores generally reflect the findings from a number of UK attitude surveys [89,94–97], as well as from various studies where social acceptance of renewables has been considered (e.g., [17,88,90]). These surveys and studies generally indicate that the UK population hold the most positive attitudes towards the use solar energy and hydro-power followed by the offshore technologies, e.g. offshore wind and marine, while smaller majorities generally hold positive attitudes towards the use of onshore wind energy and energy from biomass and waste. Studies on the social acceptability of geothermal energy [19,98] and heat pumps are very limited, particularly for the UK. It is assumed that public acceptance of heat pumps is high as this technology is mainly applied at domestic scale.

3.3. Criteria weights and preference function parameters

For this study, we are using linear preference functions (Fig. 1) for all of the criteria when comparing the different renewable technologies against each other. We furthermore assume fixed values for all of the preference function parameters and we do therefore not consider possible uncertainty in the applied preference functions. The chosen criteria-specific preference function

Table 3
Chosen preference function parameters and criteria weights.

Criterion	Preference function parameters		Criteria weights
	q	*p*	*w*
Total power generation (TW h/yr)	0	5	1/9
Maturity of technology	0	1	1/9
Reliability of energy supply	0	1	1/9
GHG emissions (g CO_2eq/kW h)	0	30	1/9
Impacts on amenity	0	1	1/9
Area requirements (m^2/kW)	0	200	1/9
Levelized energy cost (GBP/MW)	0	30	1/9
Contribution to economy	0	1	1/9
Social acceptability	0	1	1/9

Table 4
Ranking of the renewable energy technologies using fixed criteria values.

Renewable technology	**Ranking**
Onshore wind	6
Offshore wind	3
Hydro power	5
Wave	8
Tidal	7
Geothermal	9
Photovoltaic	1
Solar thermal	4
Dedicated biomass	11
Energy-from-waste	10
Heat pumps	2

parameters are given in Table 3. For all criteria, the indifference threshold parameters, q, have been set to 0. The outright preference threshold parameters, p, have been set to 1 for all of the qualitative criteria, while they have been somewhat arbitrarily specified for the quantitative criteria depending on the reported range of the corresponding criteria values. For the analysis here, we furthermore assume all the criteria to be equally important and they have therefore been assigned uniform weights, as shown in Table 3. Again, the uncertainty in the applied weights is ignored as this study specifically focusses on how uncertainties in the criteria performance values may influence the results of the MCA. However, the sensitivity of the MCA to the chosen preference function parameters and the criteria weighting could be considered through either a scenario analysis, where e.g. certain groups of criteria are arbitrarily assigned higher weights to explore environmental, social and/or economic-oriented scenarios (as commonly done, see e.g. [15,20,21]) or by assigning probability distributions to the different parameters and weights and perform Monte Carlo simulation, as suggested by Hyde et al. [99] and similar to how we treat the uncertainty in the criteria input values (see Section 3.4).

3.4. Stochastic multi-criteria analysis

To account for the uncertain criteria performance values the MCA is run using Monte Carlo simulation. For the Monte Carlo simulation, each of the criteria values in Table 2 are defined by probability density functions (pdfs), which are randomly sampled a large number of times and used as input for the MCA. Hereby a probabilistic ranking can be obtained. For the Monte Carlo simulation, all of the criteria values are assumed to be independent random variables defined by triangular probability density functions with modes equal to the best estimate values and the lower and upper bounds given by the intervals in Table 2. Because many of the criteria intervals are highly skewed (cf. Table 2), the triangular pdfs have here been transformed to symmetric triangular distributions to ensure that values on either side of the mode (best estimate) are equally likely to be sampled and avoid bias towards the tails of the distributions. The choice of triangular pdfs is somewhat arbitrary. Were more data available and had a large number of actors/stakeholders been involved in eliciting the qualitative input information, it would have been possible to fit probability distributions to this information.

4. Results and discussion

Table 4 shows the results of the MCA using the best estimate criteria values from Table 2. When all criteria are considered equally important PV, heat pumps and offshore wind come out as the best three options, while bioenergy and geothermal are the least favoured options based on the selected nine criteria. This result agrees well with the findings from a recent MCA study by Stein [21] in which biomass and geothermal were also generally found to be the least favoured renewable energy sources.

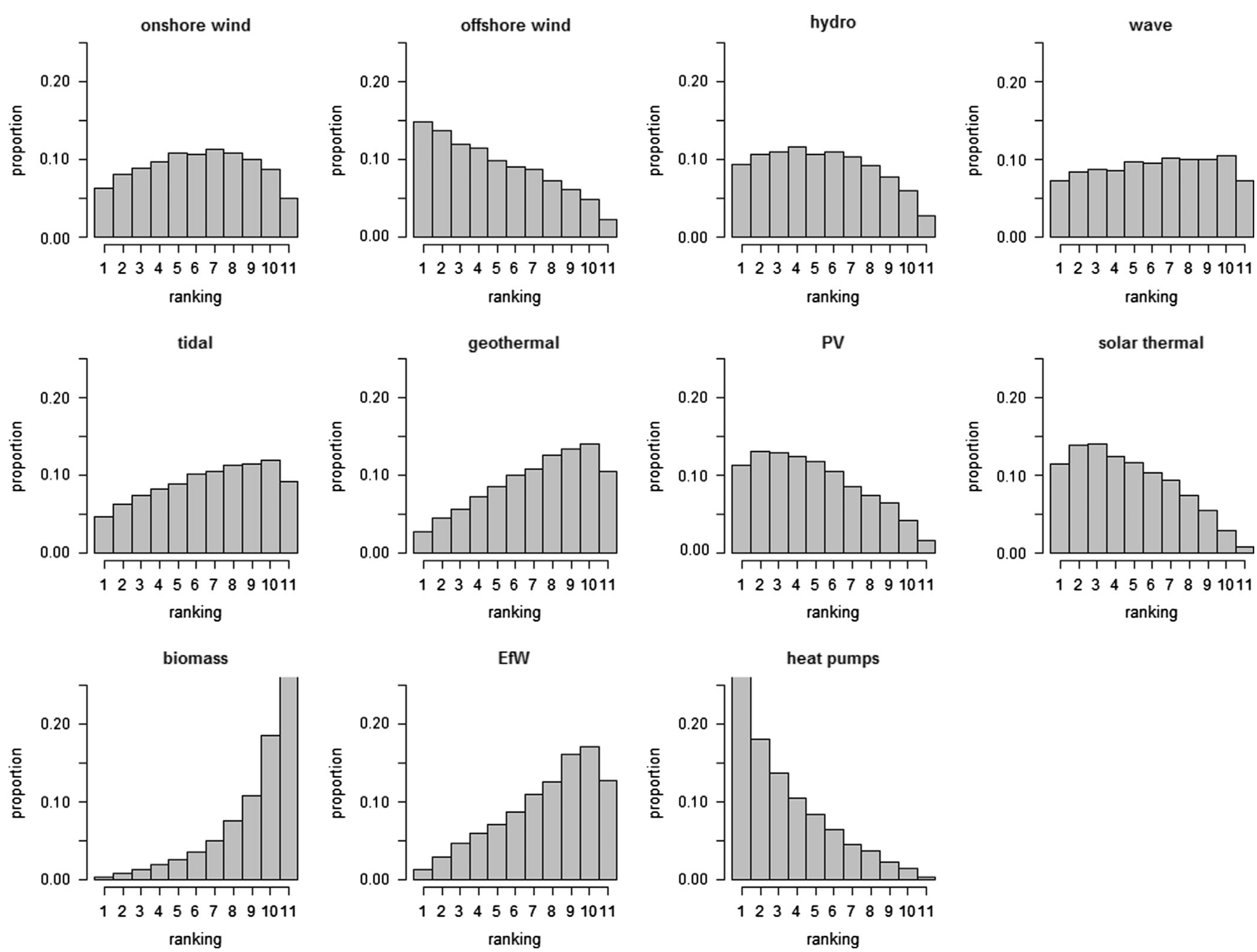


Fig. 2. Histograms showing the ranking of the selected eleven renewable energy technologies as calculated from 10,000 random MCA simulations.

Fig. 2 shows histograms of the ranking of each of the renewable energy technologies as calculated from 10,000 Monte Carlo simulations. There is a fairly clear tendency for heat pumps and also offshore wind to be amongst the most preferred options (heat pumps and offshore wind are in the top three in over 60% and 40% of the simulated cases, respectively) and for biomass and EfW of being amongst the least preferred options (biomass and EfW are in the bottom three in about 80% and 50%, respectively, of the simulated cases). However, the most striking result is perhaps just how uncertain the ranking produced by the MCA generally is with several of the technologies having very flat ranking distributions. This indicates that within the range of possible criteria values, almost any ranking of the eleven technologies is possible. In fact, all of the technologies have been found to be the most and the least favoured option in some of the simulations. While other studies have demonstrated that the ranking of renewable energy technologies is sensitive to the weights used (e.g., [15]) and to the uncertainty in the applied criteria values [99,100], the Monte Carlo approach used here shows the uncertainty in the ranking explicitly. From the probabilistic results shown in Fig. 2, a decision-maker can directly examine the sensitivity and robustness of the ranking providing her with increased confidence in which of the alternatives are the best or worst options given the selected criteria. So while the results in Fig. 2 are maybe not very surprising, they still highlight the importance of at least indicating what the potential variability in the various inputs are and show how this affects the results, just as many do with respect to the criteria weighting.

In this study, both heat pumps and solar power are generally found to perform well given the nine criteria considered. These technologies are mature with low impacts on amenity, low area requirements, high public acceptance and still have the potential to deliver relatively high energy outputs. A main problem with these technologies is their high costs, especially the capital costs, which may explain the relatively slow uptake of these technologies in the UK [101] and could suggest that these technologies should be offered greater financial incentives. Although heat pumps are a very efficient way of heating, they are generally better suited for newly-built and well-insulated houses compared retrofitting to existing and poorly-insulated properties. A shift towards an increasing use of heat pumps would also mean an increase in the demand for electricity.

Although biomass here generally is found to score poorly indicating that it may only have a limited role in the future energy picture, as it was suggested in the study by Stein [21], it can still play an important role in more site-specific energy projects. Also, the reason biomass is ranked low is mainly due to its high environmental impacts, particularly its high demand for land area, compared to the other renewable energy alternatives. However, marginal land such as brownfield sites prohibited for food production could potentially be cultivated and used for energy crop production, hereby reducing the conflict of using food crops for energy production. Growing energy crops on contaminated land may furthermore have the benefit of reducing contaminant levels in soil. Such aspects are not accounted for in this study.

Multi-criteria decision-making models, like the one developed here, can be used to assess, compare and rank different renewable energy technologies in a transparent way based on a comprehensive set of technical, environmental and socio-economic criteria. Such models can therefore be useful for informing the selection of the most suitable renewable energy technology for a given area or location and/or for guiding sustainable energy policies and financial incentives. However, the results from this study also demonstrate a clear limitation in the use of MCA for assessing and comparing the sustainability of different energy technologies and/or schemes due to the many uncertainties involved. It should be noted though that the assessment here is carried out at a national scale and is therefore quite generic, which may explain the large uncertainty associated with the criteria values and hence in the produced ranking. For actual site-specific energy projects, the degree of uncertainty is likely to be smaller. To carry out a ranking at local levels, the numbers in Table 2 should be replaced with site-specific values and the number of relevant technologies to consider would also possibly change, e.g. all of the offshore technologies would be ruled out if the specific location considered is land locked. Yet for any sustainability assessment of future energy developments, there will always be uncertainties involved. We suggest that it will rarely be possible to obtain unique rankings of renewable technologies or schemes due to the large uncertainties associated with the input data and that one therefore should be careful drawing conclusions from the results of MCA studies unless these explicitly address the associated uncertainties and sensitivities. We strongly believe that accounting for and addressing the uncertain input data explicitly by running the MCA using Monte Carlo simulation, as done here and in e.g. Hyde et al. [99], or by use of other methods such as fuzzy sets (e.g., [24]) or distance-based analyses (e.g., [102]) provides better and more robust results. We see the explicit treatment of the uncertainty, as done in our study, as a real advantage, which can lead to more informed decision-making. For example, in high-risk decision situations it will be particularly important for a decision-maker to know what the associated uncertainties with the outcomes are, while a larger degree of uncertainty may be acceptable in other decision situations.

Uncertainty is inherent in most MCAs and is not easily remediated. The uncertainty in the input information going into a MCA can be reduced through careful evaluation of the available data sources to ensure that e.g. the inputs are representative of the study context and that the underlying assumptions behind the inputs are consistent. For example, Dolan and Heath [59] show how the variability in their reviewed life-cycle GHG emission estimates from wind power systems could be reduced by 47% by harmonising the system boundaries and parameters across the studies.

In this study, only the uncertainty of the input data was considered. However, the applied weights and the preference function parameters are also subject to uncertainties, which will introduce even more uncertainty in the MCA results. A detailed sensitivity analysis of these parameters was beyond the scope of this study, but a topic for future work. Another issue not accounted for in this study and in MCAs in general is the fact that the different criteria may be correlated with each other. For example, it is likely that the impacts on amenity and the costs of the technology will affect the public's acceptance of a certain technology. Such correlations could be accounted for in the Monte Carlo simulation approach. However, to do so would require that joint probability distributions for the criteria values can be specified empirically, which generally call for vast data sets. Hyde et al. [99] demonstrate how the weights assigned to the criteria by different actors are also correlated with each other and they show how such correlation can be incorporated in their reliability-based MCA approach. Further studies on the impact of uncertainty in MCA and on how to analyse and identify which parameters and inputs affect this uncertainty the most are desired.

5. Summary and conclusion

We have developed and applied a MCA for a national-scale sustainability assessment and ranking of eleven different renewable energy technologies in Scotland. The MCA developed considers nine criteria. Extensive literature reviews for each of the selected criteria have been carried out and the information gathered has been used with MCA to provide a ranking of the

selected renewable energy alternatives. Because the input data are found to be highly uncertain, each of the criteria values has been defined by probability distributions and the MCA is run using Monte Carlo simulation. Hereby a probabilistic ranking of the renewable energy technologies is provided, which we believe is more robust for decision-making.

The assessment shows that the ranking provided by the MCA is highly uncertain and that virtually any ranking of the eleven technologies is possible due to the uncertainty in the applied criteria values. Based on this study we draw the following general conclusions:

1. MCAs are popular for assessing and comparing the sustainability of different renewable energy technologies, schemes and/or policies. However, such MCAs are generally associated with large uncertainties, particularly with respect to the applied input data. The outcomes of the MCAs will therefore also be very uncertain and obtaining a unique solution to the MCA problem will often not be possible. It is important that MCA studies address these uncertainties explicitly, when assessing the sustainability of different energy projects to obtain more robust results and ensure better informed decision-making.
2. We found that many of the applied criteria values in this study were highly uncertain and we postulate that this will be the case in most MCA studies of different renewable energy technologies and schemes. The large variation in literature values can be explained by e.g. differences in the technologies as well as regional and national differences in the renewable energy resources, infrastructure etc. There is also often a lack of transparency in how different studies arrive at different criteria values as well as inconsistent use of units, which contribute to the uncertainty. An exceptional case of this is job creation, where reported numbers can easily vary by several orders of magnitude between studies. The uncertainty is possibly exacerbated due to the generic focus of this study. For assessments at local levels of site-specific energy project, the degree of uncertainty may be significantly smaller.

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